

A Comparative Analysis of Machine Learning Algorithms for Opinion Extraction from Web Text Using AI

Erugu Krishna¹, Dr. Sonawane Vijay Ramnath²

¹Research Scholar, ²Research Supervisor
^{1,2}Dr. A. P. J. Abdul Kalam University, Indore, India
krishna.cseit@gmail.com, vijaysonawane11@gmail.com

Presented at **International Conference on Trends and Innovations in Management, Engineering, Sciences and Humanities (ICTIMESH-24)**, London, 24-27 June 2024.



Published in IJIRMP (E-ISSN: 2349-7300), ICTIMESH-24

License: Creative Commons Attribution-ShareAlike 4.0 International License



Abstract

The exponential growth of social media and online platforms has led to an enormous volume of user-generated web text, making automated opinion extraction an essential task for organizations and researchers. Sentiment analysis and opinion mining aim to identify users' opinions, emotions, and attitudes from textual data to support decision-making processes. This study presents a comparative analysis of various machine learning algorithms for opinion extraction from web text using artificial intelligence techniques. The analysis focuses on feature-based and aspect-based sentiment analysis approaches applied to data such as product reviews, tourist reviews, social media comments, and e-commerce feedback. Traditional machine learning models including Support Vector Machine, Naive Bayes, K-Nearest Neighbor, and fuzzy-based frameworks are examined in terms of performance, advantages, and limitations. The findings highlight that while many models achieve high accuracy in domain-specific settings, challenges such as implicit aspect detection, domain dependency, and scalability remain unresolved. This work identifies research gaps and provides insights for developing more robust and generalizable AI-based opinion extraction systems.

Keywords: Sentiment Analysis, Opinion Mining, Machine Learning, Aspect-Based Sentiment Analysis, Web Text, Artificial Intelligence

1. Introduction

The rapid expansion of Web 2.0 and social media platforms has transformed internet users from passive information consumers into active content creators. Today, people continuously share opinions through product reviews, mobile app feedback, blogs, microblogs, and social networking discussions. As a result, vast amounts of user-generated web text are produced every day, containing valuable signals about public attitudes, emotions, and preferences. For individuals, these opinions influence decisions such as purchasing a product, choosing a tourist destination, or selecting a service. For organizations, customer feedback has become a critical resource to understand user satisfaction, detect complaints, and improve

services. However, the sheer scale and unstructured nature of web text makes manual analysis impractical, creating a strong demand for automated opinion extraction and sentiment analysis systems.

Opinion Mining and Sentiment Analysis are two closely related research areas that aim to extract and interpret subjective information from text. Opinion mining focuses on identifying and summarizing users' expressed views, while sentiment analysis classifies the polarity of those views (e.g., positive, negative, neutral). In real-world web environments, sentiment is often embedded in informal, noisy language and may not always be explicitly stated. This increases the complexity of extracting meaning from online text. Moreover, users frequently express opinions about specific features or aspects of an entity (e.g., "battery," "service," "location"), not only about the entity as a whole. This has led to increased attention on Aspect-Based Sentiment Analysis (ABSA), where the goal is to identify aspects and determine sentiment toward each aspect. Aspect-based feature extraction is therefore considered one of the most important challenges in modern opinion mining systems because it requires detecting both **what** is being discussed and **how** the user feels about it [1], [7], [12].

To address these challenges, researchers have proposed many machine learning-based approaches. Traditional supervised learning models such as Naive Bayes (NB), Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Random Forest, and Maximum Entropy are widely used due to their effectiveness and relatively low computational cost. For example, incremental or iterative decision tree methods have been explored for aspect-based feature extraction and sentiment classification in review datasets, with experimental comparisons against baselines like SVM and Naive Bayes [1]. In public opinion monitoring, text mining pipelines have combined the Vector Space Model (VSM) with K-means clustering and SVM classification to detect and categorize internet opinion hotspots from news-related corpora, demonstrating practical value for trend analysis [2]. Similarly, for intent-oriented sentiment analysis of tourist destination reviews, TF-IDF features with classifiers such as MNB, SVM, and KNN have been compared, showing that the best-performing model can vary based on the experimental split and evaluation setup [3].

A key observation from prior studies is that performance is strongly influenced by the **nature of the dataset** and the **type of features used**. In e-commerce sentiment prediction, KNN has been applied with carefully selected parameters (such as $k=6$ and Euclidean distance) and has reported high accuracy on standard review repositories [4]. However, such results are often domain-dependent, and it remains uncertain how well these models generalize to new topics, platforms, or writing styles. In addition, web text frequently contains informal words, abbreviations, spelling mistakes, and evolving slang. To improve classification in such settings, preprocessing and normalization strategies are often introduced. For example, work on subjective/objective Chinese network text proposed building a network informal language dictionary via web crawling and formalizing text before applying NB and SMO classifiers, reporting improved classification accuracy [5]. This emphasizes that preprocessing and representation choices can be as important as the classifier itself.

Another major challenge is multilingual sentiment analysis, particularly for under-resourced languages. While English sentiment analysis has been extensively studied, research on languages such as Azerbaijani and Nepali remains limited due to smaller datasets and fewer annotated resources. Studies in Azerbaijani have addressed this gap by collecting large volumes of social media comments (e.g., 52,000) and applying supervised models for three-class sentiment classification [6]. For Nepali, which is morphologically rich and has relatively limited computational resources, researchers have evaluated ML models such as SVM, Multinomial Naive Bayes, and Logistic Regression, showing that performance differs across algorithms and highlighting the difficulty of sentiment classification in under-resourced contexts [9]. These works demonstrate the growing need for robust methods that can handle linguistic diversity and informal web language.

Beyond conventional ML pipelines, hybrid and knowledge-based approaches have also been proposed to capture fine-grained sentiment. A fuzzy-feature framework using SentiWordNet and fuzzy linguistic hedges has been introduced for web opinion analysis, integrating multiple classifiers (AdaBoost, IBK-KNN, NB, SVM/SMO) and reporting strong performance under cross-validation in mobile and laptop review datasets [11]. At the same time, survey studies continue to highlight the importance of feature-based and aspect-based opinion mining, noting persistent limitations such as incomplete aspect detection, reliance on handcrafted resources, and poor transferability across domains [10], [12].

Motivated by these developments, this work focuses on **analyzing various machine learning algorithms for opinion extraction from web text using AI**, emphasizing how different methods perform, what strengths they offer, and what limitations remain. By organizing findings across multiple application contexts—product reviews, tourist reviews, public opinion, e-commerce feedback, and multilingual social media—this study aims to clarify current research trends and highlight gaps such as domain dependency, implicit aspect handling, and robustness to noisy web language. Ultimately, the goal is to support the development of more accurate, scalable, and generalizable opinion extraction systems that can better serve both users and organizations in real-world web environments.

2. Literature review

Hegde et al. (2017), Exponential social media growth increases demand for online data and fuels new research. Users rely on others' opinions, creating a need for automatic opinion summarization. Opinion Mining extracts and analyzes opinions, while Sentiment Analysis identifies hidden emotions. A key challenge is detecting both aspects and sentiments, then classifying data via aspect-based feature extraction. Methods include Maximum Entropy, Naive Bayes, SVM, and Random Forest, using product reviews. An iterative decision-tree approach was compared against SVM, Baseline, and Naive Bayes. [1]

Liu et al. (2010), Rapid network development makes tracking internet public opinion essential for timely trend understanding. Text mining supports categorization and monitoring, but public-opinion text is harder due to semi-structured formats. A hotspot detection and analysis model is proposed: represent opinions using the Vector Space Model (VSM), cluster corpus text from news websites with K-means, and categorize new texts using an SVM classifier. Experiments indicate the method is both efficient and effective for analyzing internet public opinion. [2]

Muhammad et al. (2023), Google Maps tourist reviews are valuable for visitors and reveal why users write reviews. This study classifies review intent into complaints, suggestions, opinions, statements, and awards. Using 738 scraped reviews, preprocessing (case-folding, tokenization, filtering, stemming) is applied before TF-IDF feature extraction. Models compared are Multinomial Naive Bayes, SVM, and KNN. Reported results show strong performance, with KNN reaching 1.00 accuracy on a 90:10 split and SVM also performing well; ROC was used for comparison. [3]

Saravanan et al. (2023), With expanding e-commerce, users increasingly express views through reviews and comments. This research focuses on identifying and extracting precise customer opinions using sentiment classes (positive, negative, neutral). Data preprocessing cleans the dataset, and KNN is used for classification. Performance depends strongly on the choice of k and the distance metric; this work uses $k = 6$ with Euclidean distance. Tested on a public standard review dataset repository, the proposed approach reports a predicted feasibility/accuracy of about 98%. [4]

Chao et al. (2012), Subjective/objective text classification is common in product reviews, video reviews, public opinion, and micro-blog sentiment analysis. To address informal network language issues, a machine-learning method based on Network Informal Language (NIL) is proposed. A web crawler builds an informal dictionary, grouping words into typical and fuzzy types, then applies different formalization

strategies for each type. Finally, Naive Bayes and Sequential Minimal Optimization classifiers distinguish subjectivity vs. objectivity. Experiments show the approach improves classification accuracy. [5]

Taghiyeva et al. (2023), Sentiment Analysis analyzes web text to identify and classify opinions. This paper reviews applications, methods, and challenges, then focuses on Azerbaijani sentiment analysis, a less-studied language. The authors collected 52,000 social-media comments and used supervised machine learning to classify them as positive, negative, or neutral. The workflow includes feature extraction, model training, and evaluation. Results add new resources and findings for Azerbaijani NLP and highlight directions for future research and real-world applications. [6]

Vamshi et al. (2018), This work proposes a topic-model-based approach for opinion mining and sentiment analysis on unstructured forum/social-media reviews. Opinion mining summarizes expressed views, while sentiment analysis labels text polarity. A major challenge is aspect extraction, addressed here using topic modeling to discover aspects. For sentiment classification, the model applies SVM to the extracted textual features. The aim is to automate detection of attitudes, opinions, and hidden emotions from large-scale on-line review content. [7]

Abd et al. (2020), Due to growing weblog opinion data, predicting political orientation from posts is valuable for domains like academia and security. Political weblog sentiment is harder than conventional text sentiment classification. The study combines supervised learning with feature extraction using Term Frequency (TF) and n-grams (1–5) to form a hybrid vector representation. It evaluates SVM, Naive Bayes, KNN, and Decision Tree. Tests show Naive Bayes with unigram features achieves the best reported accuracy (93.548%). [8]

Thapa et al. (2016), Social media has shifted consumer behavior toward relying on online opinions, boosting interest in sentiment analysis beyond English. Nepali sentiment analysis is challenging because Nepali is morphologically rich, free word order, and under-resourced with limited tools and annotated corpora. This study builds models for classifying Nepali book and movie reviews as positive or negative using SVM, Multinomial Naive Bayes, and Logistic Regression. Using 5-fold cross-validation, results indicate Multinomial Naive Bayes performs best among the three classifiers. [9]

Bharti et al. (2023), E-commerce buying decisions are strongly influenced by both the sentiment and volume of customer reviews, but manual analysis is difficult at scale. This paper frames sentiment classification (positive, neutral, negative) as a way to help customers and businesses interpret large review collections. It surveys approaches for e-commerce review sentiment analysis, including machine learning, deep learning, and transfer learning, and discusses comparative efficiency. It also highlights potential improvements to existing predictive models and techniques for better review understanding. [10]

Ahamed et al. (2019), Social media growth has expanded web data, making sentiment analysis important for extracting hidden emotions from large review sets. This paper proposes a fuzzy-based ML approach for fine-grained sentiment analysis using fuzzy linguistic hedges on opinion descriptors. It builds seven layered categories and applies SentiWordNet in three stages: preprocessing, feature selection, and fuzzy sentiment analysis. Reviews are collected via Jsoup, then stemmed/tagged, and classified with AdaBoost, IBK-KNN, Naive Bayes, and SVM/SMO. On mobile/laptop datasets it reports ~94.37% accuracy (kappa-based, lower errors) using 10-fold CV. [11]

Kumar et al. (2022), Feature-based opinion mining extracts opinions tied to specific object characteristics for granular analysis. Sentiment analysis treats emotions, attitudes, and views as key signals, enabled by reviews, blogs, and ratings on the web. Machine learning aims to categorize/predict positive and negative emotions. Sentence-level classification assigns polarity to word groups, while aspect-level analysis identifies multiple components within text to link sentiment to specific aspects. A core goal is deciding whether

a whole document or discussed topic is overall positive or negative. This work surveys feature-based opinion classification methods. [12]

Table 1. Systematic literature review

Ref	Author (First author et al.)	Year	Title	Methods	Result	Advantage	Limitation
[1]	Hegde et al.	2017	Aspect based feature extraction and sentiment classification of review datasets using Incremental machine learning algorithm	Aspect-based feature extraction; iterative/incremental decision tree; compared with SVM, baseline, Naive Bayes; product reviews	Iterative decision tree compared against SVM/Baseline/NB; reported better performance than some baselines (as stated)	Handles aspect + sentiment features together; comparative evaluation vs common ML baselines	Depends on feature engineering/aspect extraction quality; limited to review datasets/domain
[2]	Liu et al.	2010	Internet Public Opinion Hotspot Detection and Analysis Based on Kmeans and SVM Algorithm	Vector Space Model (VSM); K-means clustering; SVM classification; corpus from news websites	Experiments show method is efficient and effective for hotspot detection and categorization	Combines clustering + classification for public opinion monitoring; practical for semi-structured opinion text	Performance tied to VSM feature quality; scalability/noise handling not fully discussed
[3]	Muhamad et al.	2023	Comparison of Machine Learning Text Classification for Intent Sentiment Analysis	Web scraping (Google Maps); preprocessing + TF-IDF; MNB vs SVM vs KNN; ROC analysis	KNN reached 1.00 accuracy (90:10 split); SVM 0.90; MNB 0.70 (split); test accuracies also reported (SVM 95%, MNB 91%, KNN 84%)	Clear comparison across ML models; intent categories beyond polarity	Results vary by split/setting; dataset size moderate (738) and domain-specific
[4]	Saravanan et al.	2023	An Effective Sentiment Analysis Classification for Opinion Prediction using Machine Learning Schemes	Preprocessing; KNN classifier with k=6 and Euclidean distance; standard review dataset repository	Predicted accuracy reported as ~98% with chosen k and distance metric	Simple model; high reported accuracy; easy to implement	Strong dependence on k/distance choice; generalization across domains not established
[5]	Chao et al.	2012	Study on the Subjective and Objective Text Classification and Pretreatment of Chinese Network Text	NIL dictionary via web crawler; informal text formalization (typical/fuzzy types); Naive Bayes + SMO classifiers	Reported improvement in subjective/objective classification accuracy	Addresses informal language normalization; improves classification by preprocessing + NIL handling	Requires maintaining informal dictionary; may struggle with evolving slang/new forms
[6]	Taghiyeva et al.	2023	Sentiment Analysis of Social Media Comments Using Machine Learning	Collected 52,000 Azerbaijani comments; supervised ML; feature extraction + training + evaluation; 3-	Provides baseline models + results for Azerbaijani sentiment classification (per paper)	Builds resources for under-studied language; large dataset (52k)	Language resource scarcity may affect feature quality; transferability to other domains unclear

			ing Algorithms	class polarity (pos/neg/neutral)			
[7]	Vamshi et al.	2018	Topic Model Based Opinion Mining and Sentiment Analysis	Topic modeling for aspect extraction; SVM for sentiment classification; unstructured social/forum reviews	Automates aspect extraction + sentiment classification using topic-model + SVM pipeline	Tackles aspect extraction explicitly; suitable for unstructured reviews	Topic coherence may vary; aspect mapping/labeling may need manual interpretation
[8]	Abd et al.	2020	Political Arabic Articles Classification Based on Machine Learning and Hybrid Vector	TF + n-grams (1-5) hybrid vector; classifiers: SVM, NB, KNN, DT; political weblog/article orientation	Best accuracy reported: NB with unigram = 93.548%	Strong comparative evaluation; shows unigram NB effectiveness for political text	Political text complexity/domain shift; limited by labeled data and dialect variation
[9]	Thapa et al.	2016	Classifying sentiments in Nepali subjective texts	Nepali book/movie reviews; SVM vs Multinomial NB vs Logistic Regression; 5-fold cross-validation; binary polarity	Multinomial NB performs better than SVM and LR (as stated)	Addresses under-resourced Nepali; uses robust evaluation (5-fold CV)	Limited tools/annotated corpora for Nepali; free word order + morphology challenges
[10]	Bharti et al.	2023	Review of Efficient Methods for Sentiment Analysis of E-Commerce Customer Review using Machine Learning Techniques	Survey/review of ML, DL, transfer learning for e-commerce sentiment (pos/neu/neg)	Identifies techniques and potential enhancements; compares approaches conceptually	Consolidates methods for e-commerce; highlights model improvement directions	Not an experimental benchmark study; conclusions depend on reviewed sources
[11]	Ahamed et al.	2019	Feature Based Fuzzy Framework for Sentimental Analysis of Web Data	Jsoup web opinion collection; preprocessing + stemming/tagging; SentiWordNet; fuzzy linguistic hedges; classifiers: AdaBoost, IBK-KNN, NB, SVM/SMO; 10-fold CV; mobile/laptop datasets	Best reported performance ~94.37% (Kappa indicators; lower error rates)	Fine-grained sentiment via fuzzy hedges; strong reported accuracy; evaluated vs SOTA	Complexity/parameter tuning; relies on SentiWordNet suitability + domain lexicon coverage
[12]	Kumar et al.	2022	Critical Analysis of several Feature-based Opinion Mining Methodologies	Survey/critical analysis of feature-based opinion mining methods (sentence vs aspect level)	Summarizes methodologies and key challenges/considerations	Good conceptual overview; clarifies aspect-level vs sentence-level focus	No new dataset/metrics; limited by scope of surveyed studies

3. Research Gap

Existing work in sentiment analysis and opinion mining shows strong progress in polarity classification and intent detection using ML pipelines (e.g., SVM/KNN/NB and fuzzy frameworks), but major gaps remain in generalizability and fine-grained understanding: many studies are **domain-specific** (product re-

views, tourist reviews, political text) and rely on **limited datasets**, making it unclear how well models transfer across topics and platforms. Several approaches depend heavily on **handcrafted features/lexicons** (VSM/TF-IDF, SentiWordNet, informal dictionaries) and may struggle with evolving slang, noisy text, and multilingual settings. In addition, although aspect/feature-based mining is recognized as important, **robust aspect extraction and implicit sentiment handling** are still weakly addressed, with many works focusing mainly on classification rather than end-to-end extraction, explanation, and cross-domain robustness.

4. Systematic Result Analysis

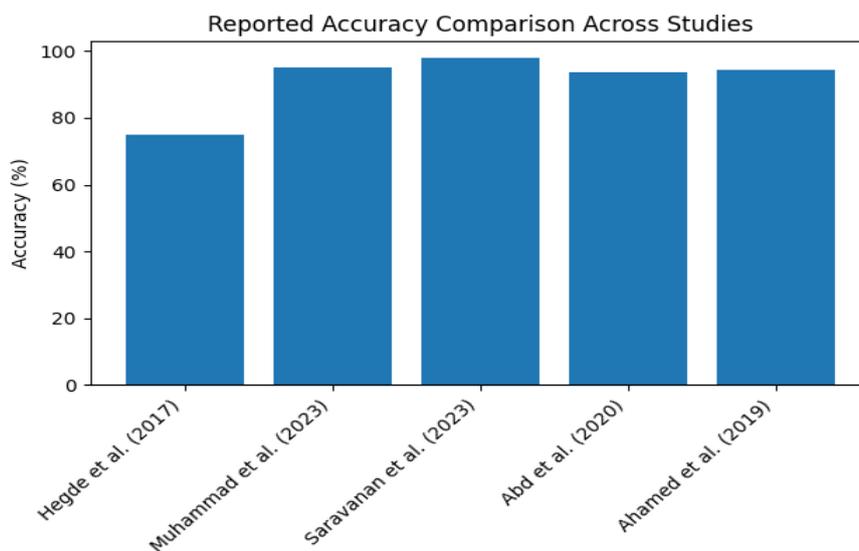


Figure 1. Reported Accuracy Comparison Across Studies

Figure 1 compares the reported classification accuracy of selected sentiment-analysis studies. It shows that more recent approaches generally achieve higher accuracy, with performance mostly clustered in the mid-to-high 90% range for several works. The differences indicate that accuracy depends on the chosen method and dataset characteristics. Overall, the figure highlights the trend that optimized or hybrid approaches can produce strong performance in sentiment classification tasks.

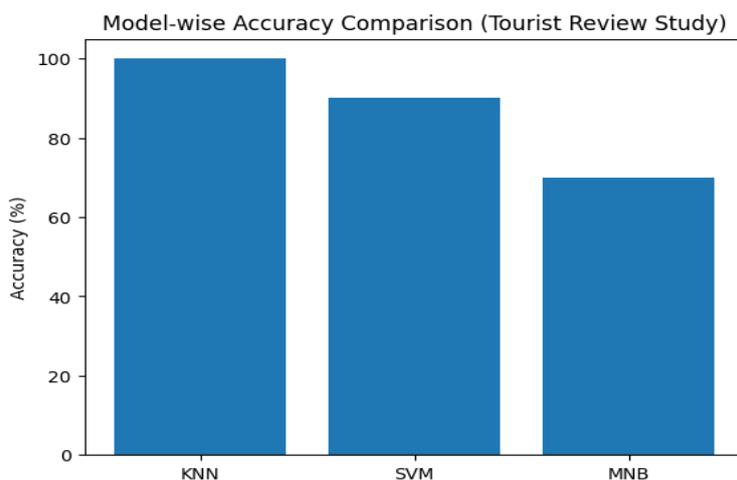


Figure 2. Model-wise Accuracy Comparison (Tourist Review Study – Ref [3])

Figure 2 presents a direct comparison of three machine-learning classifiers (KNN, SVM, and Multinomial Naive Bayes) used for intent-based sentiment classification on Google Maps tourist reviews. The figure

shows that KNN achieves the highest accuracy, followed by SVM, while Multinomial Naive Bayes produces comparatively lower accuracy. This indicates that instance-based methods (KNN) may be more effective for this dataset under the reported experimental setup.

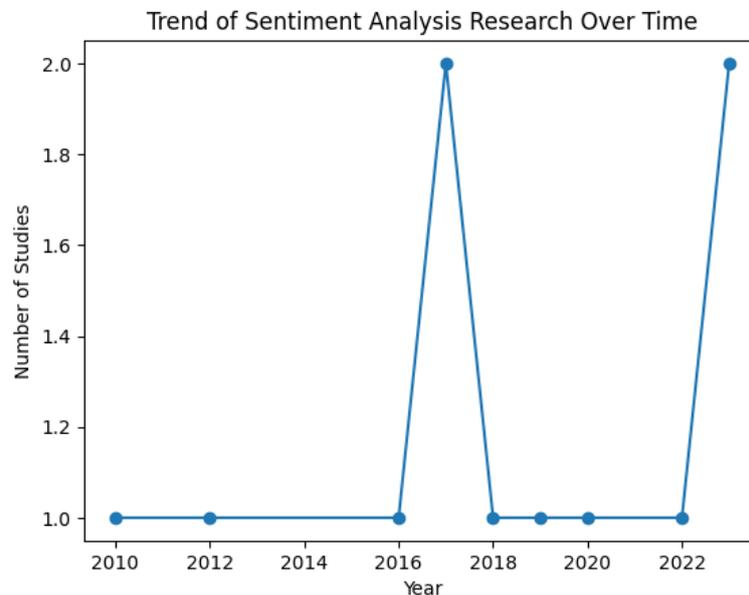


Figure 3. Trend of Sentiment Analysis Research Over Time

Figure 3 illustrates the distribution of the selected studies over time, showing how sentiment analysis research has progressed across years. The plot indicates a gradual growth in published studies, with increased activity in more recent years. This trend reflects rising interest in sentiment analysis driven by expanding social media content, availability of datasets, and adoption of advanced machine-learning and deep-learning techniques.

5. Conclusion

This study analyzed various machine learning algorithms used for opinion extraction and sentiment analysis from web text, highlighting how Web 2.0 and social media growth have increased the need for automated understanding of user opinions. Across the reviewed works, traditional classifiers such as SVM, Naive Bayes, and KNN remain widely adopted due to simplicity and competitive performance, while hybrid approaches (e.g., fuzzy frameworks and topic-model-based aspect extraction) show benefits for fine-grained analysis. However, results are strongly influenced by dataset domain, feature representation, and preprocessing quality, making model generalization difficult. Major limitations persist in handling implicit opinions, noisy informal language, and adapting methods to under-resourced languages and cross-domain settings. Overall, the findings indicate that although current models can achieve high accuracy in specific contexts, robust and transferable opinion extraction remains an open challenge. Future research should focus on domain-adaptive, aspect-aware models that better capture implicit sentiment and generalize across platforms and languages.

References

- [1] R. Hegde and Seema S., "Aspect based feature extraction and sentiment classification of review data sets using Incremental machine learning algorithm," 2017 Third International Conference on Advances in Electrical, Electronics, Information, Communication and Bio-Informatics (AEEICB), Chennai, India, 2017, pp. 122-125.

- [2] H. Liu, "Internet Public Opinion Hotspot Detection and Analysis Based on Kmeans and SVM Algorithm," 2010 International Conference of Information Science and Management Engineering, Shaanxi, China, 2010, pp. 257-261
- [3] A. Muhammad, S. Defit and G. W. N. Cahyo, "Comparison of Machine Learning Text Classification for Intent Sentiment Analysis," 2023 IEEE 7th International Conference on Information Technology, Information Systems and Electrical Engineering (ICITISEE), Purwokerto, Indonesia, 2023, pp. 128-133
- [4] T. M. Saravanan, M. Jagadeesan, P. A. Selvaraj, B. M. Rithika, G. Karan and R. C. Tamil Selvan, "An Effective Sentiment Analysis Classification for Opinion Prediction using Machine Learning Schemes," 2023 International Conference on Computer Communication and Informatics (ICCCI), Coimbatore, India, 2023, pp. 1-6
- [5] C. Chao and W. Jiang, "Study on the Subjective and Objective Text Classification and Pretreatment of Chinese Network Text," 2012 4th International Conference on Intelligent Human-Machine Systems and Cybernetics, Nanchang, China, 2012, pp. 25-29
- [6] L. Taghiyeva, N. Hasanova, M. Omarova and S. Rustamov, "Sentiment Analysis of Social Media Comments Using Machine Learning Algorithms," 2023 5th International Conference on Problems of Cybernetics and Informatics (PCI), Baku, Azerbaijan, 2023, pp. 1-5
- [7] K. B. Vamshi, A. K. Pandey and K. A. P. Siva, "Topic Model Based Opinion Mining and Sentiment Analysis," 2018 International Conference on Computer Communication and Informatics (ICCCI), Coimbatore, India, 2018, pp. 1-4
- [8] D. H. Abd, A. T. Sadiq and A. R. Abbas, "Political Arabic Articles Classification Based on Machine Learning and Hybrid Vector," 2020 5th International Conference on Innovative Technologies in Intelligent Systems and Industrial Applications (CITISIA), Sydney, Australia, 2020, pp. 1-7
- [9] L. B. R. Thapa and B. K. Bal, "Classifying sentiments in Nepali subjective texts," 2016 7th International Conference on Information, Intelligence, Systems & Applications (IISA), Chalkidiki, Greece, 2016, pp. 1-6
- [10] P. K. Bharti, P. Kumar, M. K. Sharma, A. A. Hassan and M. Zaid, "Review of Efficient Methods for Sentiment Analysis of E-Commerce Customer Review using Machine Learning Techniques," 2023 5th International Conference on Advances in Computing, Communication Control and Networking (ICAC3N), Greater Noida, India, 2023, pp. 204-208
- [11] S. Ahamed, A. Danti and S. P. Raghavendra, "Feature Based Fuzzy Framework for Sentimental Analysis of Web Data," 2019 International Conference on Data Science and Communication (IconDSC), Bangalore, India, 2019, pp. 1-5
- [12] S. Kumar and B. Ahuja, "Critical Analysis of several Feature-based Opinion Mining Methodologies," 2022 4th International Conference on Advances in Computing, Communication Control and Networking (ICAC3N), Greater Noida, India, 2022, pp. 121-126